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Airline Demand Forecasting:

Minimize forecast errors by developing an advanced booking model

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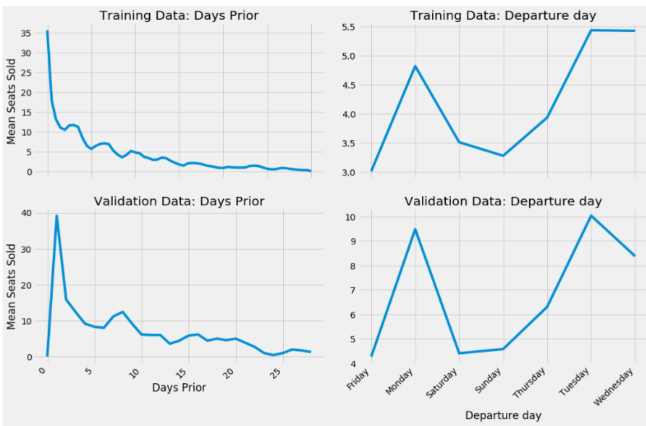
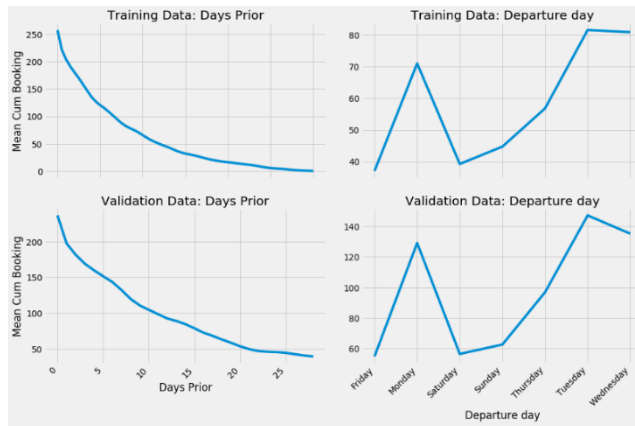
Airline Demand Forecasting

In 2017, the Global airline industry had revenues of $700 billion which is estimated to increase at an annualized rate of 3.2% to $822.5 billion by 2022, according to IBIS world. Airline revenue management relies heavily on demand forecasting to maximize its potential opportunity. Our goal is to minimize the mean absolute scaled error (MASE) of our forecast relative to the Naïve forecast in the validation data using basic additive and multiplicative models. Our multiplicative model performed best using all days prior and our additive model had the best outcome using a 3-day smoothing technique applied to the day of week. Since our data set was relatively small, we ran both additive and multiplicative model that returned the MASE value of 70.7% and 83.0%, respectively.

Additive Model: 3-day Smoothing Technique



Multiplicative Model: Used Days Prior



Algorithm Explanation

The additive model takes the average of 3 days (current, +1, and -1 day) which essentially is a smoothing technique to account for significant fluctuations between daily bookings. The multiplicative model performed best using the average of each day prior regardless of day of week. The above graphs show how and why each forecast method was determined. Although a multiplicative technique gives us an output MASE of 83.0%, an additive model gave us a more accurate result of 70.7%. Initially, the additive model averaged the seats sold for each day prior bookings and had a MASE of 214%. We averaged using departure day of week, since different days of the week have different booking characteristics. While this decreased our MASE, we ultimately saw that the 3-day smoothing technique minimized the effects of daily fluctuations for the booking days to account for the booking patterns of business travelers and travel agents.

From “main()”, our “airlineForecast” function starts by calling the function “readCSV” to load the training and validation data as dataframes. The training dataframe is passed to “calculateDaysPrior” to calculate the days between booking_date and departure_date. The function “calculateDailyBookings” calculates the additional bookings per day and the 3 day average. The training dataframe is then passed to ‘calculateAverageDailyBookings’ and ‘calculateAverageDailyBookingsRate’ to setup the day of week data frame (using “createDOWDataFrame”) for the additive and multiplicative models respectively. Lastly, our main function “airlineForecast” applies the day of week dataframes to the validation data to calculate our additive and multiplicative forecasts. Our MASE and predicted forecasts as dataframes are returned to the “main()” function in a list.